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Community structure in resting state complex networks

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Analysis of resting state functional magnetic resonance imaging (rs-fMRI) using graph theory is of increasing interest. Here, brain regions are represented as nodes and links between nodes are present if the statistical dependence of the time courses exceeds a given threshold. So-called communities can be found as clusters of nodes with high internal linking and sparse linking to the rest of the network and the degree to which a network can be divided into such communities can be measured using the modularity index [1]. Modularity has shown to be related to e.g. normal aging [2], working memory [3], and motor learning [4]. However, it is still unknown whether modularity reflects the best grouping of nodes. Here we use the Infinite Relational Model (IRM) [5,6] and two constrained variants thereof and test their clustering reproducibility and ability to predict unseen data.

Three rs-fMRI datasets were used. The Copenhagen set was acquired locally and consists of 30 healthy controls (HC), TR=2.49s, 480 vol. In addition we used two datasets from the FCON1000 database. The Leipzig set consists of 37 HC, TR=2.3s, 195 vol. and Beijing Zhang part2 sets consists of 42 HC, TR=2s, and 225 vol. Data preprocessing included realignment and normalization to MNI305 space. The Copenhagen data was filtered using physiological (cardiac, respiration, motion) regressors [7]. The mean time series for each of the 116 brain regions included in the AAL atlas [8] was extracted for each subject and their correlation matrix was formed. The brain networks were created by thresholding these matrices individually to maintain the top d-percent links (Fig. 1).

IRM is a nonparametric Bayesian Network model, which can be used to infer node clustering. Contrary to modularity, the IRM models both within-cluster and between-cluster link probabilities. Therefore nodes with a high internal linking could in fact be clustered separately if their relation to other clusters is different. By placing a Chinese Restaurant Process (CRP) prior on the node partitioning the number of clusters is determined during the model inference. A Beta distribution is used as prior for the cluster link probabilities, these probabilities can however be integrated out and thus model inference only involves sampling the node cluster assignments using Markov chain Monte Carlo. Here we seek common node clustering and cluster link probabilities over subjects. In addition we consider two

constrained versions of the IRM. The Bayesian Community Detection (BCD) [9], which for a given cluster restricts between-cluster link probabilities to be strictly lower than the within-cluster link probability. The Infinite Diagonal Model (IDM) allows individual within-cluster probabilities but restricts all between-cluster link probabilities to be equal. IDM can thus be seen as a probabilistic version of modularity. The NPAIRS [10] split-half framework was used to evaluate the models predictability and reproducibility for different graph link densities (2, 4, 8, 16, and 32%). Predictability was measured using test likelihood of data from one split when the model was trained on the other split. Predictability was calculated as the normalized mutual information between node partitions of the two splits.

For all link densities and datasets investigated BCD and IRM showed clearly better predictability than IDM and BCD had better or on par predictability compared with IRM (Fig. 2). For link densities greater than 4% IRM and BCD had higher reproducibility than IDM, and BCD had better or on par reproducibility compared with IRM.

Resting state organization in fMRI networks is consistent with a model based on community structure. Modelling between-cluster linking significantly increases predictability and reproducibility. Node partitioning and link probabilities together represent a compressed description of the network, which allows for group inference, behavioral measures correlation, and is a potential new expressive bio-marker.

Figure 1

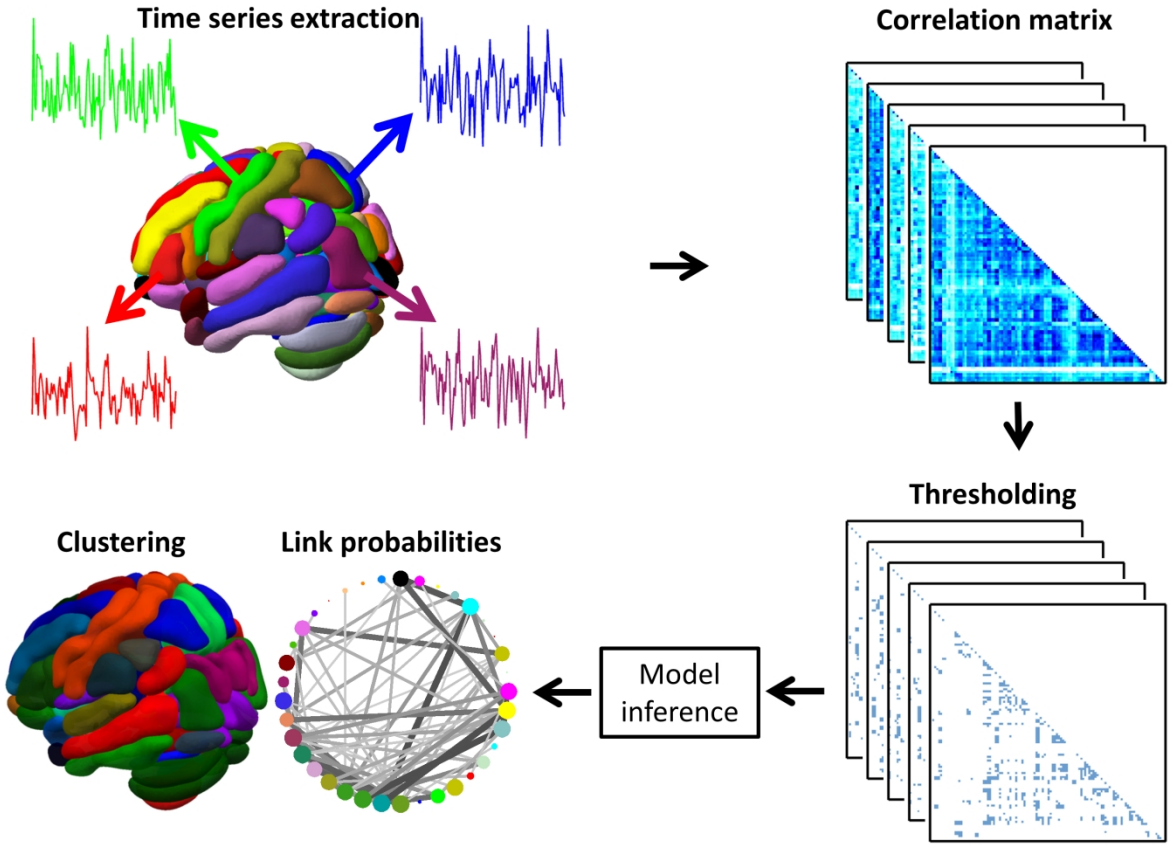
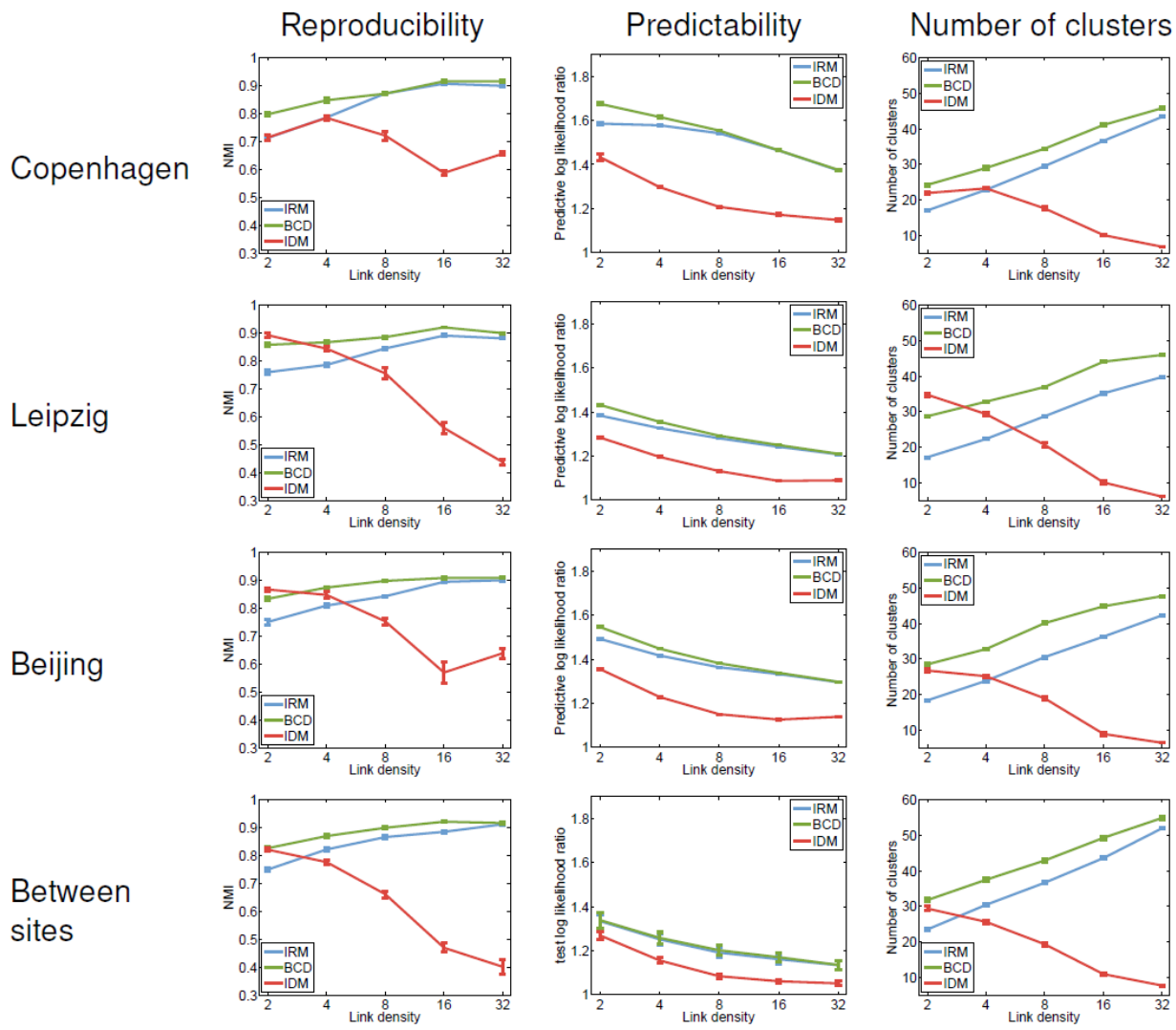

Time series extraction
Correlation matrix
Thresholding
Model inference
Link probabilities
Clustering

Figure 2


Reproducibility
Predictability
Number of clusters
Copenhagen
Leipzig
Beijing
Between sites
NMI
Predictive log likelihood ratio
test log likelihood ratio
Number of clusters
Link density
IRM
BCD
IDM

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